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James Lewis Crooks[1,2], Wayne E. Cascio[1], Madelyn S. Percy[3], Jeanette Reyes[4], Lucas M. Neas[1], and Elizabeth D. Hilborn[1]

[1]Environmental Public Health Division, National Health and Environmental Effects Research Laboratory, U.S. Environmental Protection Agency, Chapel Hill, North Carolina, USA; [2]Division of Biostatistics and Bioinformatics, National Jewish Health, Denver, Colorado, USA; [3]Department of Geological Sciences, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA; [4]Department of Environmental Sciences and Engineering, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA

Address correspondence to James L. Crooks, Division of Biostatistics and Bioinformatics, National Jewish Health, 1400 Jackson Street, Denver, CO 80206-2761 USA. Telephone: 303-398-1543. E-mail: CrooksJ@njhealth.org

Running title: Dust storms and mortality in the United States

Abstract

Background: The impact of dust storms on human health has been studied in the context of Asian, Saharan, Arabian, and Australian storms, but there has been no recent population-level epidemiological research on the dust storms in North America. The relevance of dust storms to public health is likely to increase as extreme weather events are predicted to become more frequent with anticipated changes in climate through the 21st century.

Objectives: To examine the association between dust storms and county-level non-accidental mortality in the United States from 1993 through 2005.

Methods: Dust storm incidence data, including date and approximate location, are taken from the U.S. National Weather Service storm database. County-level mortality data for the years 1993-2005 were acquired from the National Center for Health Statistics. Distributed lag conditional logistic regression models under a time-stratified case-crossover design were used to study the relationship between dust storms and daily mortality counts over the whole U.S. and in Arizona and California specifically. Endpoints included total non-accidental mortality and three mortality subgroups (cardiovascular, respiratory, and other non-accidental).

Results: We estimated that for the US as a whole total non-accidental mortality increased by 7.4% (95% CI: 1.6, 13.5; $p = 0.011$) and 6.7% (95% CI: 1.1, 12.6; $p = 0.018$) at 2- and 3-day lags, respectively, and by an average of 2.7% (95% CI: 0.4, 5.1; $p = 0.023$) over lags 0-5 compared to referent days. Significant associations with non-accidental mortality were estimated for California (lag 2 and 0–5 day) and Arizona (lag 3), for cardiovascular mortality in the U.S. (lag 2) and Arizona (lag 3), and for other non-accidental mortality in California (lags 1–3 and 0–5.)

Conclusions: Dust storms are associated with increases in lagged non-accidental and cardiovascular mortality.

Introduction

Dust storms affect many parts of the world, including North Africa and the Sahel, southern

Europe, the Middle East, central and East Asia, Australia, and the western United States. The US

EPA has concluded that short-term exposures to ambient particulates adversely affect

cardiovascular health, and are likely to have respiratory health effects (U.S. E.P.A. 2009).

Beyond the direct effects of particulates on the body, dust storms can impact human health via

decreased road visibility and interaction with microscopic organisms such as fungi and bacteria.

Specific outcomes include asthma, tracheitis, pneumonia, allergic rhinitis, silicosis, stroke,

conjunctivitis, skin irritation, meningococcal meningitis, coccidioidomycosis (valley fever), as

well as health impacts related to toxic algae and automobile accidents (Goudie 2014).

Little epidemiological research has been published on the health impacts of dust storms in the

U.S. since 1999. In that year a study of 17 dust storms in the Spokane, Washington area that

found no increase in the risk of non-accidental death due to dust storms (Schwartz et al. 1999).

Since then, though, there has been no population-level study of dust storms as a general

phenomenon in the U.S. Instead, recent work in the U.S. has focused on linking dust storms to

specific health endpoints such as valley fever (Comrie 2005), neurotoxic shellfish poisoning and

pulmonary symptoms resulting from algal blooms (Fleming et al. 2011) associated with Saharan

dust deposits (Walsh and Steidinger 2001).

However, since 1999 there has been growing worldwide interest in measuring the health impacts

of dust and dust storms. Much of the recent research has focused on the impact of Gobi Desert

dust incursions on the countries of East Asia: South Korea, Japan, Taiwan, and China (Chen et

al. 2004; Yang et al. 2005; Chen et al. 2004; Chen and Yang 2005; Yang et al. 2005; Chiu et al.

2008; Chan et al. 2008; Lee et al. 2013). There has also been growing interest in the health

impacts of airborne Saharan dust in southern Europe (Middleton et al. 2008; Samoli et al. 2011;

Tobias et al. 2011; Zauli Sajani et al. 2011; Karanasiou et al. 2012; Neophytou et al. 2013;

Alessandrini et al. 2013) as the health impacts of coarse particles (e.g., Perez et al. 2009) have

come to be recognized. Additionally, there has been notable work on dust storms in other dust-

affected parts of the world including Australia (Merrifield et al. 2013), Israel (Vodonos et al.

2014; Vodonos et al. 2015), Kuwait (Thalib & Al-Taiar, 2012; Al-Taiar & Thalib, 2014), and the

Caribbean (Gyan et al. 2005). The positive associations found in many of these works suggest a

need to revisit North American dust storms.

Methods

U.S. Mortality

We acquired mortality data from the National Center for Health Statistics (NCHS)

(http://www.cdc.gov/nchd/deaths.htm). The NCHS data consists of individual-level extracts of

the original death certificates collected and retained by state and local governments. The NCHS

mortality data are held by EPA's National Health and Environmental Effects Research

Laboratory (NHEERL) under a limited data use agreement.

The data were acquired in 2007 and thus provide daily records from January 1, 1985 through

December 31, 2005, or 7670 unique days. They cover all 50 U.S. states, the District of

Columbia, Puerto Rico, and U.S. territories. Data elements for each individual death record

include county of residence, date of death, age, sex, race, and multiple causes of death. Between

1985 and 1998 the cause-of-death information was encoded according to the ninth revision of the

International Classification of Diseases (ICD-9), while the tenth revision (ICD-10) was used

between 1999 and 2005 (http://www.cdc.gov/nchs/icd.htm).

Daily counts for non-accidental death as well as the three non-accidental subcategories

(respiratory, cardiovascular, and other non-accidental) were tabulated according to the date and

primary cause listed for each death. Non-accidental mortalities are categorized under ICD-9

codes 000-799 and ICD-10 codes A000-R999. Respiratory mortality corresponds to ICD-9

codes 480-486, 490-497, and 507, and to ICD-10 codes J100-J118, J120-J189, J209-J499, and

J690-J700, while cardiovascular disease falls under ICD-9 codes 390-448 and ICD-10 codes

I000-I799. Non-accidental mortalities not falling into either the respiratory or cardiovascular

disease subcategories were categorized as other non-accidental.

Dust Storms

In the United States, areas that are common sources of dust include salt flats, like those in

Nevada and Utah, exposed limestone, common in Arizona, New Mexico, and throughout the

Basin and Range province, and dune fields, like those found in Colorado and New Mexico. Due

to varying wind directions driven by the position of the jet stream and seasons, dust sources can

affect large population centers.

There is no consistent meteorological classification for dust storms, and because of technical

challenges associated with sampling particulates when ambient concentration are high (The

National Academies of Sciences, Engineering, and Medicine, 2010), storm identification based

on particulate concentrations may not be accurate. For the present study we use dust storms as

reported in the U.S. National Weather Service (NWS) storm database. This information comes

from a variety of sources including emergency management officials, law enforcement, skywarn

spotters, damage surveys, media reports, the insurance industry, and the general public

(https://www.ncdc.noaa.gov/stormevents/faq.jsp). The NWS does not guarantee the accuracy of

information in the database, and the only location information provided is the NWS weather

forecast zone in which each storm is reported. However, this database is the most complete

storm record that exists for the U.S.

Our primary analysis evaluated associations between dust storms and mortality based on data for

1993–2005, but we also present a descriptive analysis of the characteristics of US dust storms

based on data from 1993–2010, including an analysis of the association between monitor-based

PM_{10} concentrations and dust storms. We downloaded a subset of the National Weather Service

storm database containing 846,377 storm events between January 1, 1950 and March 31, 2011.

Extracting all storms with event types that included the word "Dust", specifically, "DUST

STORM", "BLOWING DUST", "HIGH WINDS DUST STORM", "DUST STORM/HIGH

WINDS", "DUSTSTORM", "Saharan Dust", and "SAHARAN DUST" left 393 unique storm

events. The earliest such event was recorded in 1993, which we believe reflects a change in

reporting rather than an absence of dust storms prior to 1993. We excluded storms occurring in

US territories (Puerto Rico and the U.S. Virgin Islands), two dust storm events in the Eastern

U.S. (in Indiana on May 23, 2005 and Delaware on May 18, 2000) that involved dust blown

from recently tilled farm fields, and three storms that occurred in early 2011, resulting in 378

storms for the descriptive analysis of storm characteristics. The primary mortality analysis

included a total of 209 storms through 2005.

Air Pollution and Meteorological Data

We downloaded the 24-hour average PM_{10}, $PM_{2.5}$ (particles with aerodynamic diameter ≤ 2.5 μm), and ozone ambient monitor data for the years 1993-2010 from the EPA Air Data website (http://www.epa.gov/airdata/ad_data_daily.html). Monitor-based daily meteorological variables were downloaded from the National Climate Data Center (http://www.ncdc.noaa.gov).

Dust Storms and Individual PM_{10} Monitors

Because the storm database includes data from sources of varying quality, our first set of exploratory analyses investigated whether dust storms reported in it are associated with increased observed ambient concentrations of PM_{10}. We therefore looked at the association between dust storms and ambient PM_{10} concentration at the level of individual monitors in the years 1993-2010. Because our primary analysis concerns county-level mortality we investigate the county-level association between dust storms and PM_{10} (among other air pollution and meteorological variables) in a later section.

First, we mapped the forecast zones using the NOAA forecast zone shape file dated March 16 2006 (http://www.nws.noaa.gov/geodata/catalog/wsom/html/pubzone.htm). Next, we determined which forecast zones held observed dust storms using the storm database, then extracted the PM_{10} monitors falling into these zones using the `over` function in `sp` package (Bivand et al. 2013) (All analyses in this paper were performed in the R language (R Core Team, 2015) version 3.1.3 unless otherwise specified). We then reduced each of the remaining monitors' time series to those days on which a dust storm was reported in the zone containing the monitor, and to control days defined as those days in the same month falling and on the same day of the week as the storm. Thus, if the storm was reported on a Tuesday in May 1998 we

7

compared that day's monitor concentration to concentrations on the 3 or 4 other Tuesdays in May 1998.

We estimated the association between PM_{10} concentrations and dust storm events using a mixed effects model with PM_{10} concentration as the response, dichotomous dust storm event and as the fixed effect, and a random intercept and slope. A separate random effect strata was defined for each combination of storm and monitor, with each strata containing the monitor's storm day and its 3 or 4 control days. We performed this analysis first using all monitors lying in the storms' weather forecast zones and then using only the subset of rural monitors (as defined by the U.S. EPA) to explore the influence of anthropogenic PM sources on our results.

Assigning Storms to Counties

Because the mortality counts in our health study were localized to counties rather than specific addresses we needed a method for assigning storms observed in a forecast zone to the counties overlapping that zone. The criteria we used for assigning a dust storm to a given county was whether the county overlapped at least 10% of the spatial area of the storm's weather forecast zone (the impact of varying this threshold is explored in the Results). Thus a storm event occurring in a single forecast zone could be assigned to more than one county depending on the relative geometries of zones and counties. On 11 occasions a forecast zone experienced two dust storms in a single day; these were treated as a single event for the purposes of the health study.

Counties were mapped using the 2010 census shape file (http://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html). Overlap areas were calculated using the gIntersects and gArea functions in the rgeos (Bivand & Rundel, 2014) package in R. While there were several county

boundary changes in the U.S. between 1985 and 2010, none affected counties overlapping

weather forecast zones in which dust storms were reported.

Dust Storms and County-Average Air Pollution and Meteorology

The county containing each monitoring station was determined through ArcGIS 10.2.1

(Environmental Systems Research Institute, 2011). For all pollutants and meteorological

variables, monitors were excluded if they did not meet certain criteria (Bell et al. 2007). If a

monitor operated less than 6 months or had fewer than 30 observations all data from said

monitor were removed. For $PM_{2.5}$ there was also a correlation criterion: If there existed a monitor

that had less than 0.80 correlation with the majority of the remaining monitors within the same

county all data associated with that particular monitor were removed. PM_{10} had no such

correlation criterion. The daily average within a given county was calculated through a system of

standardizing values (Schwartz 2000). Once county-level temperature was calculated, a heat

wave index was created which classified heat waves according to whether the mean temperature

reached or exceeded the 98th percentile of daily mean temperature in that location for two or

more days consecutively (Anderson and Bell 2011).

To further investigate relationships between pollutants, meteorological variables, and dust storms

we fitted a mixed effects model to each pollutant and meteorological variable with a fixed effect

for storm and random effects for intercept and storm. A separate random effect strata was

defined for each unique combination of storm assigned county. We used the same method of

selecting control days that we used in the monitor-level comparison of dust storms and PM_{10}

above. Thus each strata consisted of the storm day together with the 3-4 days in the same month

with the same day-of-week.

Dust Storms and Mortality

For our primary analysis the county-level mortality, dust storm, air pollution, and meteorological data were merged together. Because we are interested in lagged associations of dust storms on mortality we created new county-level mortality, air pollution, and meteorological variables for lags 0 to 5 days. Then in each county we retained data from the day of the storm, the 3-4 other days in the same month with the same day-of-week, and their respective lag days. Only mortalities occurring on one of these days contribute to the partial likelihood used to estimate the health association in the next section. This method of selecting days to retain for analysis is similar to the method used in our exploratory analyses above except that now we also retain lag days.

Our mortality analysis used a time stratified case-crossover design (Maclure 1991) in which each deceased individual serves as her or his own control. This design assigns a separate strata to each mortality event and the days defining its reference set; the specific day of the individual's death within the reference set is considered the random event. We defined the reference set for a given individual mortality as those days within the same month, year, and county as the mortality and falling on the same day-of-week (Janes et al. 2005). Each reference set thus included at least one storm day or lagged storm day, though the mortality associated with the reference set did not necessarily occur on a storm day (it is vital to the design that some do not). This design implicitly controls for all confounders that either do not vary or vary slowly relative to the time period defined by the reference set, such as county, state, season, year, and the race and sex of the deceased.

We used distributed lag conditional logistic regression models adjusted for average county-level daily temperature (modeled as a natural spline with three degrees of freedom) to estimate the difference in mortality on dust storm days versus referent days. We performed our analyses using the clogit function in the survival package (Therneau, 2015). Our primary analysis included a dichotomous dust storm variable for each lag day (lags 0-5) and average county-level daily temperature. Since the association between temperature and mortality is known to be nonlinear, temperature was represented with a natural spline with three degrees of freedom. All confidence intervals are reported at the 0.05 significance level. P-values greater than 0.05 are interpreted as indicating no association.

After removing records with missing confounder data, followed by strata with no reported mortalities, 141 unique county-level storm events remained. Arizona had the largest number of storms, followed by California.

Confounding

We investigated the impact of confounding of our primary dust storm association by five meteorological or air pollution variables: precipitation, heat waves, and ambient $PM_{2.5}$, PM_{10}, and ozone concentrations. These variables were chosen because they are associated with dust storm events or are known to have independent associations with mortality. Potential confounders are described as having no qualitative impact on the primary results if the associations estimated while controlling for the confounder are found to be within 10% of (and in the same direction as) the associations from the primary analysis, and the same lag days are statistically significant.

Effect Modification

Effect modification was assessed using the likelihood ratio test to compare models with and without a multiplicative interaction between the putative modifier and the lagged dust storm indicator variables. A p-value above 0.1 was interpreted as indicating no evidence for effect modification.

We tested for effect modification by precipitation. Dust storms can be generated at the leading edge of thunderstorms and thus can precede rainfall, though only about 15% of county-level storm events were associated with more than 0.1 inches of precipitation. Still, precipitation could plausibly modify the relationship between dust storms and non-accidental mortality by reducing ambient dust concentrations after the storm, or if dust storms co-occurring with precipitation are stronger or weaker than others.

We also tested for effect modification by day of week, region of the country (the regions being Arizona, California, Mountain Region (Nevada and Utah), Plains Region (Texas, Oklahoma, Nebraska, Kansas, Colorado, and New Mexico), and Northwest Region (Washington State, Idaho, Oregon, and Montana)), year, calendar month, hour of the day the storm was first observed, and observed storm duration. The region in which the storm takes place could modify the storm association if there were a higher implicit detection threshold in regions with higher background. There could be effect modification by day of week due to differences in observers' or exposed individuals' activity patterns. Effect modification by year could indicate changes in dust storm reporting over the study period. Because these changes may not be linear in time we tested for year as a linear trend and also as a categorical variable with three levels (1993-1998; 1999-2002; 2003-2005). Effect modification by calendar month could indicate seasonal

differences in human behavior patterns affecting exposure or reporting, in dust-associated weather patterns, or in mineral and/or biological content. Storms of longer duration could have stronger health associations. The same could be argued for storms occurring during rush hour; hence, we tested hour of first observation as both a linear and a nonlinear trend using a natural spline with 3 degrees of freedom.

Sensitivity Analyses

We tested the sensitivity of our results by varying the data processing and modeling choices used in our primary analyses in three ways.

First, we checked for sensitivity to the temperature specification by checking whether our results were impacted by replacing the natural spline fit with three degrees of freedom to two alternatives: a natural spline fit with two degrees of freedom and a three-level categorical variable split by tertiles of temperature (≤ 60 °F, 61-85 °F, and ≥ 86 °F).

Second, we performed a separate, independent analysis within each of the five geographic regions defined above (using the same statistical model as in our primary analysis), and then used the mvmeta meta-analysis package (Gasparrini et al. 2012) in R to aggregate to the national level. Even without direct evidence of effect modification by region it is still possible that the assumptions in our model are too strong with respect to geographical differences.

Third, we re-ran our primary model under three variations on the 10% overlap threshold used to assign each forecast zone to counties. We assigned each forecast zone to all counties overlapping at least 5% of the zone, to all counties overlapping at least 25% of it, and also to the single county with the maximum overlap. We did not run models with a 50% overlap since

many forecast zones in the western U.S. do not have a 50% overlap with any county and there

would have been substantial loss of power.

Results

Descriptive Analysis

The number of dust storms reported to the National Weather Service has increased over our

study period (Figure 1A), though, it is uncertain whether this increase reflects a true increase or a

change in reporting behavior. The region over which dust storms were reported encompasses

much of the mountain West with a tail extending into north Texas and Oklahoma (Figure 2).

Figure 1C summarizes the distribution of dust storms by state over the period 1993-2010.

Arizona had the most with 182, followed by California (70), Washington and Nevada (32),

Texas (18), and Oregon (13). However, the total number of storms occurring up through 2005

(and thus available for our mortality study) was 209. The largest numbers occurred in Arizona

(77), California (55), Washington (21), Nevada (17), and Oregon (10). The average annual

number of reported dust storms was therefore higher in the period 2006-2010 (33.8) than during

the period 1993-2005 (16.0) or even 2001-2005 (28.0). Figure 1B shows the distribution of

reported dust storms across calendar months. While dust storms occurred in all twelve calendar

months the largest number occurred in the spring and summer, with July having the most.

Figures 1D and 1F show the number of storms detected and the number of storms ongoing,

respectively, in each hour of the day. Dust storms in the storm database are most likely to appear

in the early afternoon, though with significant numbers forming from late morning to evening.

Only a handful are reported between 10pm and 6am. Figure 1E shows the distribution of storm

durations. Nearly half of storms last less than 1 hour, though the distribution has a long right tail

with 7 storms lasting over 12 hours.

Dust Storms and Individual PM$_{10}$ Monitors

Nationally, dust storms were associated with a 77.6 µg/m^3 increase (95% CI: 59.8, 95.4; $p < 10^{-16}$) in 24-average PM$_{10}$ concentration, with a similar association found when using rural monitors

only (75.8 µg/m^3; 95% CI: 35.3, 116.3; $p = 0.0003$) (Supplemental Material, Table S1).

Corresponding models for natural log-transformed PM$_{10}$ indicated a 99.1% increase (95% CI:

83.6, 115.9, $p < 10^{-16}$) and 81.3% increase (95% CI: 45.8, 125.4; $p < 10^{-16}$), respectively

(Supplemental Material, Table S1).

Dust Storms and County-Average Air Pollution and Meteorology

County-level data indicate that during 1993–2005 the mean county-level PM$_{10}$ concentration on

dust storm days and control days together was 49.5 ± 105.3 µg/m^3 (median 31.0 µg/m^3) (Table

1). County-level PM$_{10}$ concentration was the variable most strongly correlated with dust storms

($\rho = 0.302$), followed by barometric pressure ($\rho = -0.215$).

Results from the mixed effects models are given in Table 2. Dust storms were associated most

strongly with temperature (1.61 °F increase), dew point temperature (1.50 °F increase),

atmospheric pressure (2.89 mb decrease), and most importantly PM$_{10}$ (74 µg/m^3 or 110%). Thus

there remains a strong association between PM$_{10}$ and dust storm variables at the level of

aggregation in which these variables will appear in the health models. Dust storms were not

significantly associated with PM$_{2.5}$ concentration, humidity, precipitation, or heat waves.

Dust Storms and Mortality

Our primary analysis included a total of 141 storm events and 49,427 deaths and during lags 0–5

in the US as a whole, 65 storms and 22,838 deaths in Arizona, and 41 storms and 23,918 deaths

in California (Table 3). Almost half of the deaths were classified as cardiovascular (20,074 in the

US as a whole), while only 4,719 deaths were classified as having a respiratory cause.

For the U.S. as a whole we estimated a 7.4% increase in non-accidental mortality at lag 2 (95%

CI: 1.6, 13.5; $p = 0.011$), a 6.7% increase at lag 3 (95% CI: 1.1, 12.6; $p = 0.018$), and a daily

mean increase of 2.7% over lags 0-5 (95% CI: 0.4, 5.1; $p = 0.023$) compared to control days

(Figure 3). In Arizona, which contains 46% of the dust storms in our sample, we found an 8.6%

increase at lag 3 (95% CI: 0.83, 17.0; $p = 0.029$) but no other statistically significant

associations. In California we found a 13.2% increase at lag 2 (95%CI: 4.0, 23.2; $p = 0.004$) and

a daily mean increase of 6.4% over lags 0-5 (95% CI: 2.6, 10.3; $p = 0.0007$).

We then investigated the three subcategories of non-accidental mortality. There were no

significant associations between dust storms and respiratory mortality at any lag for the whole

U.S., Arizona, or California, though numbers of deaths were the smallest for this outcome

(4,719, 2,022, and 2,431 deaths, respectively) (Supplemental Material, Figure S1). However, we

estimated a 9.5% increase in cardiovascular mortality at lag 2 for the whole U.S. (95% CI: 0.31,

19.5; $p = 0.042$) and a 13.0% increase at lag 3 in Arizona (95% CI: 0.40, 27.1; $p = 0.043$)

(Supplemental Material, Figure S2). For other non-accidental mortality, there were significant

positive associations for deaths in California at lag 1 (16.8%, 95% CI: 3.2, 32.3; $p = 0.014$), lag 2

(20.7%, 95% CI: 6.7, 36.5; $p = 0.0028$), and lag 3 (15.2%, 95% CI: 2.0, 30.1; $p = 0.022$), and 0-5

day mean lag (10.9%, 95% CI: 5.2, 16.8; $p = 0.00012$) (Supplemental Material, Figure S3).

16

Confounding

Controlling for confounding by precipitation, heat waves, and PM_{10} concentration had no qualitative impact on our primary results for total non-accidental mortality (Supplemental Material, Table S2). For $PM_{2.5}$, though, including it in our merged data set reduced the number of complete cases, cutting the number of usable dust storms from 141 to 96 and decreasing the average number of control days per strata. Consequently, associations between dust storms and non-accidental mortality for the whole U.S. were estimated only for lag 2 (15.8%; 95% CI: 5.6, 27.1; $p = 0.0018$) (Supplemental Material, Table S2). However, with this smaller complete-case data set the results were insensitive to whether $PM_{2.5}$ was included as a variable in the statistical model, suggesting that differences between these and the full results above may be due to sample size rather than to confounding by $PM_{2.5}$. For example, the lag 2 result for the primary model applied to the $PM_{2.5}$ complete cases data was 15.6% (95% CI: 5.4, 26.8; $p = 0.0021$) (Supplemental Material, Table S2). Monitoring for ozone is somewhat more complete than for $PM_{2.5}$, yielding 103 usable dust storms. However, despite the smaller sample size, controlling for ozone concentration had no qualitative impact on our primary results (Supplemental Material, Table S2).

Effect Modification

for effect modification by precipitation (Supplemental Material, Table S3). In our primary analysis we choose to report the impact of dust storms as a total weather system rather than reporting results modified by precipitation. This is a conservative choice; the dust storm associations with mortality at zero precipitation are higher in magnitude and have a lower p-value than the overall associations. We did not find evidence for effect modification by the other

variables we tested (day of week, region of the country, year, calendar month, hour of the day the

storm was first observed, and observed storm duration); p-values for the corresponding

likelihood ratio tests are given in Supplemental Material, Table S3.

Sensitivity Analyses

Differences between the dust storm associations estimated using alternative temperature

specifications and those of the primary analysis were relatively small. For example, the total

non-accidental mortality associations at lag 2 were 7.5% (95% CI: 1.7, 13.7; $p = 0.011$) with

categorical temperature and 7.6% (95% CI: 1.7, 13.8; $p = 0.010$) with the two degree of freedom

spline, compared to 7.4% (95% CI: 1.6, 13.5; $p = 0.011$) for the primary analysis.

Associations for the US as a whole based on a meta-analysis of region-specific model estimates

were weaker than associations based on our primary analysis (Supplemental Material, Figure

S4). However, the national meta-analysis still yielded a significant dust storm association with

total non-accidental mortality at lag 3 (7.35%; 95% CI: 1.69, 13.3; $p = 0.010$) and with

cardiovascular mortality at lag 2 (10.1%; 95% CI: 0.86 20.3; $p = 0.032$). Under the primary

analysis these associations were 6.7% (95% CI: 1.1, 12.6; $p = 0.018$) and 9.5% (95% CI: 0.31,

19.5; $p = 0.042$), respectively.

Using 5% and 25% forecast zone overlap thresholds yielded results that were generally slightly

stronger than the primary analysis (Supplemental Material, Figure S5). For example, the

national non-accidental mortality associations at lag 2 were 7.61% (95% CI: 1.85, 13.7; $p =$

0.0090) at 5% overlap and 7.99% (95% CI: 2.16, 14.2; $p = 0.0066$) at 25% overlap. However,

the model run assigning each zone to the single county with the maximum overlap yielded

attenuated results; however, significant associations were still apparent for total non-accidental

mortality at lag 2 over the whole U.S. (7.16%; 95% CI: 0.79, 13.9; p = 0.027) and in California

(14.6%, 95% CI: 3.88, 26.4; p = 0.0065), and for the daily mean over lags 0-5 in California

(5.64%; 95% CI: 1.23, 10.2; p = 0.012). The observed attenuation may reflect the 15-20% fewer

mortalities yielded by this assignment method compared to the others (Supplemental Material,

Table S4), for example 39,885 non-accidental mortalities using the maximum overlap method

compared to 49,427 using the 10% overlap method.

Discussion

We found that days on which dust storms occurred were associated with a 7.4% increase in total

non-accidental mortality at lag 2, a 6.7% increase at lag 3, and a mean daily increase of 2.7%

over lags 0-5 compared to control days. These results are backed up by a lag 3 increase in

Arizona as well as lag 2 and mean 0-5 lag increases in California. While no associations were

found for respiratory mortality, we did find associations for cardiovascular disease mortality at

lag 2 nationally and lag 3 in Arizona, as well as for other non-accidental mortality in California

at lags 1, 2, and 3, and mean lags 0-5. The absence of an association for respiratory mortality

may simply be due to the small number of mortalities in that category (Table 2).

Comparable epidemiological studies from around the world have yielded mixed results. In East

Asian, an early study in Taipei City did not find significant associations with mortality (Chen et

al. 2004), in contrast to the positive associations found in our study. However, a more recent

study (Lee et al. 2013) estimated increases in population-level daily mortality due to

cardiovascular causes at lag 0 (2.91%) and lag 5 (3.7%) and due to total non-accidental causes at

lag 3 (1.57%). While their work did find significant associations in similar mortality categories

as ours, the lags at which associations were observed differed, with the exception of non-accidental death at lag 3.

The evidence for associations with clinic visits and hospital and emergency department admissions in East Asia is likewise mixed. (Yang et al. 2005) and (Chan et al. 2008) estimated significant associations between Asian dust storms and hospital admissions for stroke and cardiopulmonary emergency department admissions, respectively, for Taipei City. However, studies of other types of hospital-related outcomes in Taipei City have yielded null associations (Chen et al. 2004; Chen and Yang 2005; Yang et al. 2005; Chiu et al. 2008).

For Saharan dust incursions, a 2012 review (Karanasiou et al. 2012) found no evidence in the literature of an association between $PM_{2.5}$ and total or all-cause mortality during incursion events in southern Europe, but reported mixed results for PM_{10} and coarse (between 2.5 and 10 μm) PM concentrations. However, a more recent study in Cyprus (Neophytou et al. 2013) inferred a significant positive association between daily cardiovascular mortality and dust storm-related PM_{10} at lag 0. Saharan dust clouds were also estimated to be positively associated with asthma admissions on the Caribbean island of Trinidad (Gyan et al. 2005).

Further studies in Europe have focused on effect modification by Saharan dust. Incursions were found to exacerbate the impact of coarse PM on respiratory disease hospital admissions and of PM_{10} on cerebrovascular disease admissions in Rome, Italy (Alessandrini et al. 2013), of coarse PM on total mortality in Madrid, Spain (Tobias et al. 2011), and of PM_{10} on cardiovascular and all-cause hospital admissions in Nicosia, Cyprus (Middleton et al. 2008). Effect modification by dust event has also been reported for the PM_{10} association with mortality in Athens, Greece, though in the negative direction (Samoli et al. 2011), possibly indicating higher toxicity for

20

traffic-related particles than for dust particles in that area. Furthermore, while Saharan dust

events were not estimated to modify the association between PM_{10} and daily mortality in the

Emilia-Romagna region of Italy there was evidence for a main association of Saharan dust on

respiratory mortality in the elderly (Zauli Sajani et al. 2011).

The handful of studies in the Middle East have estimated associations with hospitalizations but

not mortality. A series of papers focusing on the population of Beer-Shiva, a city in southern

Israel, estimated significant associations of dust storms and dust-storm related PM_{10} with

hospitalizations for COPD exacerbations (Vodonos et al. 2014) and acute coronary syndrome

(Vodonos et al. 2015). Similarly, studies of dust storms in Kuwait estimated associations with

increased asthma and respiratory hospital admissions (Thalib & Al-Taiar, 2012). However, the

same researchers found no associations with respiratory, cardiovascular, or all-cause mortality at

lags 0, 1, 2, 3, and 5 (Al-Taiar & Thalib, 2014).

The breadth of results found in different parts of the world may reflect differences in the size or

susceptibility of the exposed population, the magnitude of exposure, the choice of health

outcome and study design, the availability of confounder data, the chemical and/or biological

composition of airborne dust, the dust storm definition, or the number of storms observed. This

suggests a need for more coordination between researchers when planning studies, larger

(possibly multi-national) study populations and better characterization of dust composition. The

MED-PARTICLES project (MED-PARTICLES 2010) provides a regional-scale example of

such coordination. Their recent study of 13 cities across Southern Europe (Staffogia et al.)

estimated mortality associations of similar magnitude for both desert-derived PM_{10} and PM_{10}

from other sources.

In light of the positive associations estimated in many of these studies, our goal was to revisit the

relationship between dust storms and mortality in the United States. The fact that our work

inferred positive associations between dust storms and mortality while Schwartz and colleagues

(Schwartz et al. 1999) did not may be due either to the difference in sample size between the two

studies (141 vs. 17 storms) or to the fact that their work did not study delayed associations past

lag 1.

Our study exhibits a number of strengths. First, it is the first population-level epidemiological

study of dust storms in the U.S. since 1999 and is broader in geographic and temporal scope than

previous work. Second, the data features a sufficient number of storms and mortalities to allow

investigation both national-level mortality associations as well as state-level associations in the

two states with the largest number of recorded storms. Third, the study utilizes a case-crossover

design that automatically controls for confounders that vary between counties or on timescales

longer than a month.

Our study also has a number of limitations. First, the dust storms listed in the National Weather

Service storm database are not detected or reported using a consistent protocol. There may be

variations over time, between weather forecast offices, and between individual observers.

However, our sensitivity analyses were unable to identify factors beyond precipitation that

systematically affect our results. Second, the lack of storm severity information or location

information at finer resolution than the weather forecast zone leaves open the possibility that we

included minor storms unlikely to impact health. This could limit the sensitivity of our study to

correctly identify a storm association representative of significant storms by classifying

individuals as exposed when they are not and biasing our results toward the null. Third,

assigning a dust storm to all counties overlapping at least 10% of the weather forecast zone in

which it is reported may limit sensitivity for similar reasons. However, our results were not

strongly dependent on this threshold, which we varied from 5% to 25% with little impact. Using

only the county with the maximum overlap instead did attenuate our results somewhat, though

many associations remained detectable; the difference may simply reflect sample size. Fourth,

by construction our study design could not detect mortality associations more than five days

removed from a storm so could not address chronic dust exposure. Fifth, the lack of daily $PM_{2.5}$

monitoring over much of the country means we could not study confounding by $PM_{2.5}$ without

substantial loss of power; that being said, when we ran our models on the subsample of days with

complete $PM_{2.5}$ data we found no evidence of confounding.

We have shown, at both the monitor level and county level, that dust storms are strongly

associated with increased ambient PM_{10}. The presence of a dust storm association even when

controlling for county-average ambient PM_{10} concentration suggests either that the mortality

response to dust exposure is nonlinear in exposed concentration, that county-average ambient

PM_{10} concentrations do not fully reflect the concentrations experienced by storm-affected

populations, or that there is a different physiologic response to storm-related dust compared to

other ambient particles.

The fact that we found associations between mortality and dust storms, and between dust storms

and PM_{10}, but not between dust storms and $PM_{2.5}$, suggests that our health associations are

driven either by the coarse fraction of PM or by a difference in composition of fine particles on

storm days compared to other days (ambient concentrations on dust storm days likely have a

lower anthropogenic fraction than concentrations on other days). While our work is not designed

to address the difference between total and coarse PM directly, our results do underscore the

concerns expressed in (Sandstrom and Forsberg 2008) that the toxicity of the coarse fraction of

desert dust has not been sufficiently characterized.

Conclusions

We find evidence for a positive association between U.S. dust storms and non-accidental,

cardiovascular, and other non-accidental mortality. We also find evidence for associations in the

two states with the highest dust storm incidence, Arizona and California. Our results suggest

that natural dust emissions present a more pressing public health problem in the United States

than has been appreciated. They argue for improved public health information campaigns and

early warnings systems.

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Table 1: Descriptive statistics for county-average meteorology and air pollution variables, 1993-2005.

Atmospheric Variable	Unit	Number of Observations	Mean ± SD	Median	Max	Correlation
PM$_{2.5}$	µg/m^3	271	13.7 ± 10.2	10.0	74.3	-0.042
PM$_{10}$	µg/m^3	404	49.5 ± 105.3	31.0	1438	0.302
Ozone	ppb	570	51.0 ± 13.9	50.8	108.5	-0.021
Temperature	F	1008	69.2 ± 17.4	69.3	106	0.036
Dew Point Temperature	F	1003	42.1 ± 14.0	41.8	78.9	0.042
Relative Humidity	%	1003	41.3 ± 17.7	38.4	97.8	-0.029
Precipitation	inches	998	0.021 ± 0.083	0	1.020	0.016
Barometric Pressure	mb	866	1013.0 ± 5.6	1012.4	1036.0	-0.215
Heat Wave Index		1013	0.023 ± 0.149	0	1	0.044

Number of Observations refers to the number of days on which dust storms were observed in a given county plus each storm's control days (the same day of week and in the same month and county as the storm). The Mean, SD, Median, Max, and Correlation were computed over this set of days. Correlation refers to the Pearson correlation between the atmospheric variable and an indicator for dust storm event. A total of 304 county-level storm events are included; this number is larger than the 209 storms observed during 1993-2005 because some storms are assigned to multiple counties.

Table 2: Summary of random effects models relating county-average meteorological and air pollution variables on days with dust storms to control days, 1993-2005.

Atmospheric Variable	Unit	Coefficient (95% CI)	p-value
PM$_{2.5}$	μg/m^3	-0.48 (-3.19, 2.23)	0.70
log(PM$_{2.5}$)		0.0025 (-0.1692, 0.1743)	0.97
PM$_{10}$	μg/m^3	74 (27, 121)	6.7×10^{-4}
log(PM$_{10}$)		0.741 (0.488, 0.994)	2.7×10^{-9}
Ozone	ppb	-0.69 (-2.79,1.41)	0.46
Temperature	°F	1.62 (0.55, 2.69)	8.5×10^{-4}
Dew Point Temperature	°F	1.50 (0.13, 2.86)	0.014
Relative Humidity	%	-1.26 (-3.39, 0.87)	0.19
Precipitation	inch	0.0032 (-0.0121, 0.0185)	0.64
Barometric Pressure	mb	-2.89 (-3.75, -2.04)	1.7×10^{-12}
Heat Wave Index		-6.3 (-19.2, 6.6)	0.27

The Atmospheric Variable serves as the response variable. Each model includes a dust storm indicator as the sole fixed effect and separate random intercept for each strata (consisting of a storm day and its control days). A total of 304 county-level storm events are included; this number is larger than the 209 storms reported during 1993-2005 because some storms are assigned to multiple counties.

Table 3: Number of county-assigned storm events and total number of mortalities on dust days and control days, by geographic area, 1993-2005.

Total Non-Accidental	Number of Storms	Number of Mortalities
U.S.	141	49427
Arizona	65	22838
California	41	23918
Cardiovascular		
U.S.	139	20075
Arizona	64	8639
California	41	10402
Respiratory		
U.S.	120	4719
Arizona	52	2022
California	40	2421
Other Non-Accidental		
U.S.	137	24633
Arizona	65	12177
California	41	11095

Non-accidental mortalities encompass ICD-9 codes 000-799 and ICD-10 codes A000-R999. Respiratory mortality corresponds to ICD-9 codes 480-486, 490-497, and 507, and to ICD-10 codes J100-J118, J120-J189, J209-J499, and J690-J700, while cardiovascular disease falls under ICD-9 codes 390-448 and ICD-10 codes I000-I799. Location "U.S." refers to the 50 U.S. states plus the District of Columbia. Number of Storm Events varies by mortality cause because only those storms that have at least one mortality in the given cause category in that storm event's reference set (0-5 days after the storm and referent days) are included.

Figure Legends

Figure 1: The number of reported dust storms (1993-2010) in the U.S. (as listed in the National Weather Service storm database) by: (A) year, (B) month, (C) state, (D) hour of the day, (E) observed duration, and (F) hour of first observation. These numbers include storms in the period 2006-2010 that are not included in the primary health analysis. Due to reporting errors or biases the number of reported storms may not represent the true number of dust storms that occurred.

Figure 2: National Weather Service Forecast Zones colored by the number of reported storms (1993-2010). Zones without reported dust storms are not colored. This figure includes storms from the period 2006-2010 that are not included in the primary health analysis. Satellite data were downloaded from Google Maps (Google, Inc, 2015) on May 15, 2015 using the ggmap package (Kahle and Wickham, 2013) in R.

Figure 3: Percent increase in total non-accidental mortality associated with dust storms, compared to control days, by location and lag, for the years 1993-2005. Non-accidental mortalities fall under ICD-9 codes 000-799 and ICD-10 codes A000-R999. Associations are estimated using a distributed lag model for dust storm events with non-linear control for temperature (natural spline with 3 degrees of freedom). Note that the y-axes limits differ between locations.
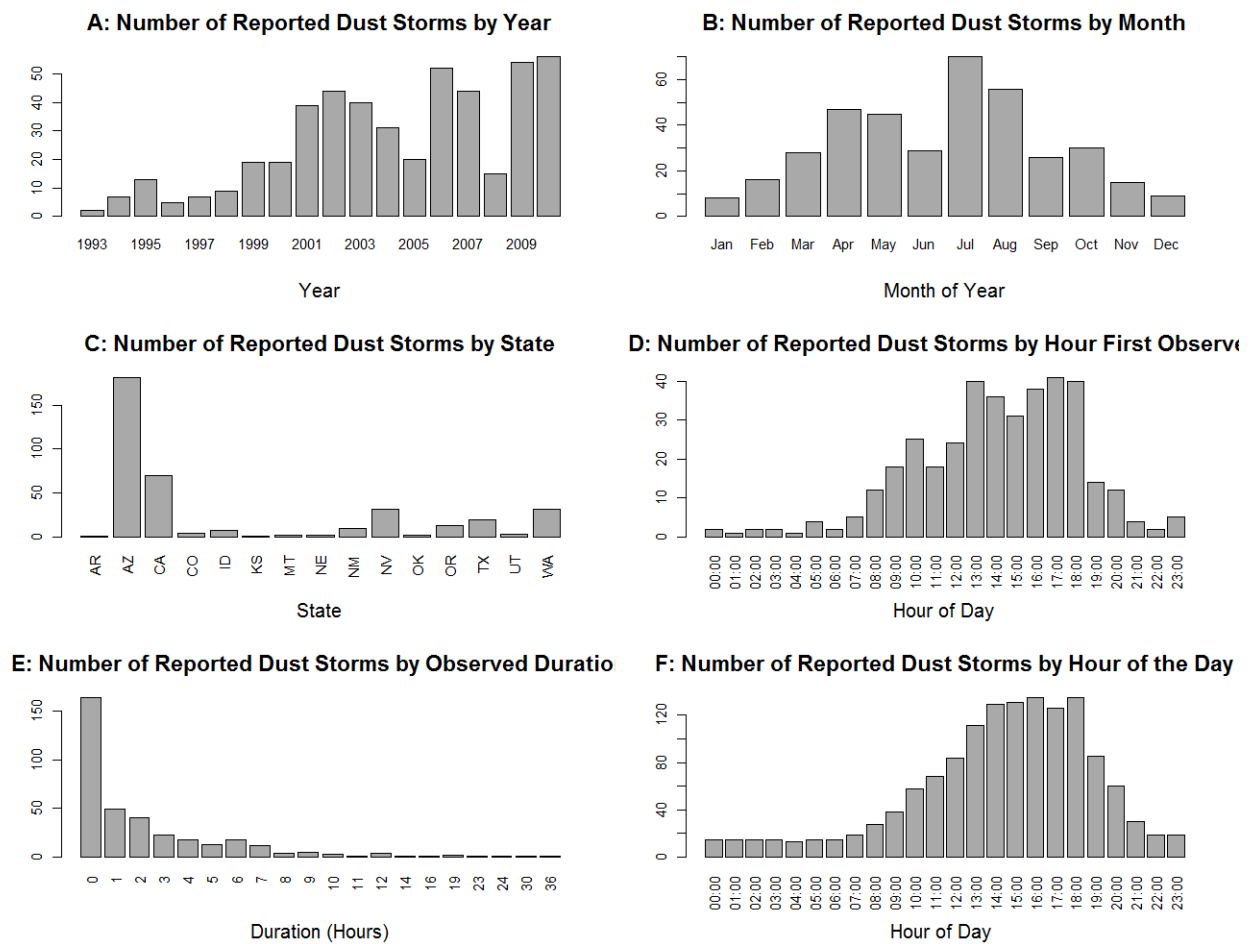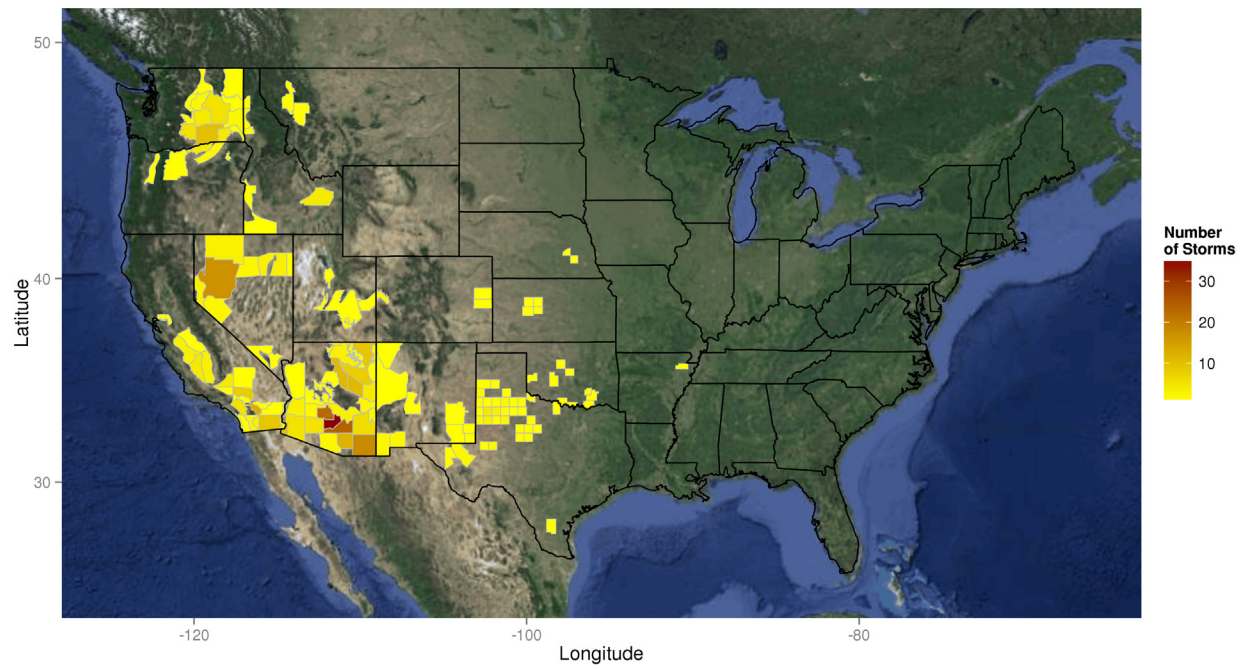
Figure 1.

Figure 2.

Figure 3.